DEVELOPING TURFGRASS WATER RESPONSE FUNCTION AND ASSESSING VISUAL QUALITY, SOIL MOISTURE AND NDVI DYNAMICS OF TALL FESCUE UNDER VARYING IRRIGATION SCENARIOS IN INLAND SOUTHERN CALIFORNIA

Research

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HIGHLIGHTS

- A turfgrass water response function was developed for 'Westcoaster' tall fescue.
- The Weathermatic smart controller demonstrated reliable estimations of reference evapotranspiration.
- Restricting irrigation frequency did not yield water savings or lead to improvements in turfgrass quality.

ABSTRACT. *Efficient landscape irrigation is an important water conservation strategy and reduces strain on limited water resources in inland Southern California. A three-year field irrigation trial was conducted in Riverside, California, to evaluate the response of 'Westcoaster' tall fescue (Festuca arundinacea Schreb.) to a wide range of autonomous irrigation scenarios implemented using a Weathermatic smart controller. The response of the turfgrass was assessed using visual rating (VR) and normalized difference vegetation index (NDVI) data collected with a handheld sensor. These experimental data were then used to develop a regression-based turfgrass water response function (TWRF), which was further employed to estimate the response of tall fescue to different irrigation levels during years with varying atmospheric evaporation demands, including extreme conditions. A strong correlation was observed between NDVI and VR (r = 0.88). A minimum NDVI threshold of 0.7 was identified to maintain an acceptable level of tall fescue quality for residential areas. During the trial periods, irrigation application rates below 100% of reference evapotranspiration (ET_o) were insufficient to sustain the desired quality of tall fescue. The TWRF estimations suggested that 60% ET_o can be applied for short periods (7 to 43 days, depending on the atmospheric evaporative demands) during the summer before the visual quality drops below the minimum threshold. Comparing different irrigation strategies, it was observed that on-demand irrigation, which adjusts irrigation frequency based on ET_o demand, resulted in higher NDVI and VR values compared to a limited watering schedule of only a few days per week. Analysis of soil moisture data revealed that the primary root water uptake occurred mainly in the topsoil layer (<33 cm), and the applied irrigation water primarily replenished the shallow soil layer (<20 cm) due to the coarse sandy loam soil characteristics. The Weathermatic controller, equipped with on-site air temperature measurements, provided reliable ET_o estimations and can be used for autonomous landscape irrigation scheduling in semiarid regions.*

Keywords. *Evapotranspiration, Remote sensing, Smart irrigation controller, Urban irrigation, Water conservation.*

The western USA is generally arid and subject to droughts while being home to some of the largest cities in the nation. The significant demand for landscape irrigation, high population, and dependency on water transportation from other regions make urban water conservation critical in southern California. Most water agencies in the region offer rebate programs to encourage the adoption of smart controllers in residential areas to increase landscape irrigation efficiency (Singh et al., 2020).

Several case studies have reported the water-saving benefits of ET-based smart controllers compared to fixed timer-based irrigation (Davis and Dukes, 2010; Davis et al., 2009; Davis and Dukes, 2016; Devitt et al., 2008). Additionally, Bijoor et al. (2014) studied the water budgets of lawns in southern California and found that smart sensors were a more effective option for enhancing irrigation efficiency compared to the choice of turfgrass species. In the United States, most scholarly research projects focusing on the reliability of smart controllers have been conducted in humid areas, primarily to avoid excessive irrigation (Dukes, 2012).

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Consequently, field-based research studies are limited on the application of smart controllers for landscape deficit irrigation in semi-arid regions.

Turfgrass is an urban feature with the potential for water conservation. It is a significant component of the urbanized land area, including residential, commercial, and institutional lawns, parks, golf courses, and athletic fields. Turfgrass serves important recreational purposes and provides valuable ecosystem services such as capturing runoff, alleviating the urban heat island effect, and reducing dust (Brosnan et al., 2020). Therefore, it is crucial to determine the minimum water requirement to maintain the aesthetic quality of commonly planted cool-season and heat- and drought-tolerant warm-season turfgrass species.

Weather conditions have a significant impact on the response of turfgrass to deficit irrigation strategies. However, field research trials are conducted for a limited number of years, which may not capture the long-term variations in weather conditions. To address this limitation, we have recently introduced the turfgrass water response function (TWRF) as an empirical regression-based model. This model allows us to estimate the response of turfgrass species, based on aesthetic values, to varying irrigation applications and atmospheric evaporative demands (Haghverdi et al., 2021c). Using the TWRF, we have successfully estimated the response of hybrid bermudagrass [‘Tifgreen’ *Cynodon dactylon* (L.) Pers. ×*C. transvaalensis* Burtt-Davy] in southern California to a wide range of irrigation strategies, considering long-term fluctuations (30-40 years) in reference evapotranspiration (ET_o) demands. The results showed that hybrid bermudagrass can withstand prolonged periods of stress in years with relatively low atmospheric evaporative demand (Haghverdi et al., 2021c).

Visual rating (VR), ranging from 1 (worst) to 9 (best), is traditionally used by researchers and managers worldwide for turfgrass evaluation and to assess its response to different irrigation scenarios (Leinauer et al., 2014). However, due to its subjective nature, this method can be inaccurate and non-reproducible, and ratings are prone to inconsistencies between different observers or even for an identical evaluator over time (Bell et al., 2002; Horst et al., 1984). An alternative approach is remote sensing crop indices, such as the normalized difference vegetation index (NDVI), which provides an overall evaluation of turfgrass quality, growth, and health. Additionally, VR is time-consuming and cannot be automated; therefore, remote sensing is a more practical approach for rapid scouting and monitoring drought injury in large irrigated areas, such as parks and golf courses. (Hong, Bremer, & van der Merwe, 2019) demonstrated that high-resolution drone-based remote sensing can detect drought stress more than 5 days before it becomes apparent to human observers. The reported results in the literature (Bremer et al., 2011a,b) suggest that in most cases, NDVI is well correlated with turfgrass VR values. However, the relationship between NDVI and VR varies for different turfgrass species and cultivars and should be separately established across different climate conditions.

The primary goal of this project was to advance autonomous landscape irrigation management in semi-arid regions using ET-based smart controllers. The project specifically focused on two main aspects: (I) comparing "on-demand" irrigation with frequency restriction scenarios, and (II) assessing the reliability of reference evapotranspiration (ET_o) estimations based on on-site air temperature measurements over non-standard surface conditions. The study was designed to achieve three specific objectives. Firstly, to monitor and analyze the response of tall fescue (*Festuca arundinacea* Schreb.) and observe soil moisture fluctuations over time under varying irrigation levels and frequencies in inland southern California. Secondly, to develop and implement a regression-based TWRF that can determine the minimum irrigation application for autonomous ET-based irrigation of tall fescue during periods with extremely high and low atmospheric evaporative demands. Our ongoing and future research involves conducting multiple irrigation trials in inland Southern California, with a particular focus on warm-season turfgrass and alternative groundcover species.

Materials and Methods

Study Area

A three-year field research trial was conducted from 2017 to 2019 at the University of California Riverside Agricultural Experiment Station (33°57'47.0"N 117°20'13.4"W) in Riverside, California, with a focus on autonomous irrigation management of 'Westcoaster' tall fescue. Figure 1 provides an illustration of the layout of the experimental plots and an overview of the research plots in early 2018.

The soil at the research site is classified as a well-drained, low-runoff Hanford coarse sandy loam (https://websoilsurvey.sc.egov.usda.gov/). Based on the laboratory analysis of four undisturbed soil samples collected from the top 20 cm using the HYPROP-WP4C (METER Group Inc., WA) system, the volumetric soil water content was determined to be 0.30 m^3 m^{-3} at 10 kPa and 0.10 m^3 m^{-3} at 1500 kPa (Haghverdi et al., 2020).

Table 1 summarizes the meteorological variables for the study site, which were obtained from the California Irrigation Management Information System (CIMIS) weather station 44, located approximately 250 m away from the experimental plots. Riverside has a semi-arid climate, with a 36-year mean annual ET_o of 1476 mm and rainfall of 223 mm. Analysis of long-term weather data at the study site revealed that the cumulative ET_o from May to October accounts for more than 65% of the annual ET_o demand, while only 10% of the total annual rainfall is typically received during this period. The minimum and maximum cumulative ET_o during the experimental seasons were observed in 2017 and 2018, respectively.

Irrigation Trial

A total of 36 plots, each sized 3.7 m × 3.7 m, were utilized for this study. To prevent interference between adjacent plots, an approximate border of 60-90 cm was maintained. The establishment of the irrigation system and instrumentation was conducted over a four-month period from January to April 2017. Each plot was equipped with a Hunter PGV-101G solenoid valve (Hunter Industries, Inc., San Marcos, CA, USA), which controlled the water supply. The irrigation

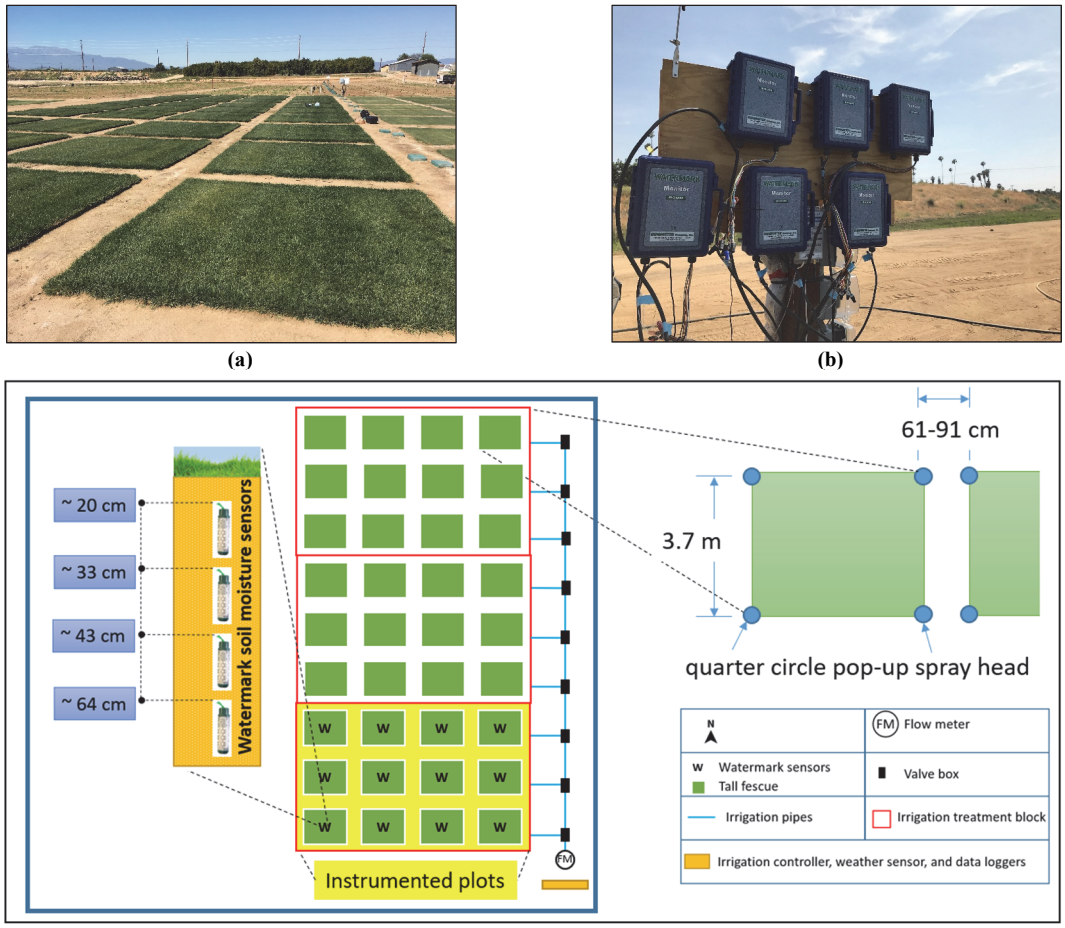

Figure 1. A photo taken on 3/28/2018 showing an overview of the research plots (a) and Irrometer M600 data loggers collecting data from 48 soil moisture sensors installed in 12 plots (b). The layout of the experimental plots (c).

Table 1. Meteorological parameters for the experimental site.[a]

	ET_o (mm day^{-1})	CP (mm)	SR (W m^{-2})	Ta (ºC)	RH (%)	WS (m s^{-1})
2017-Trial	4.9	12	237.7	24.3	60.6	1.8
2018-Trial	5.8	8	299.3	23.1	56.4	1.8
2019-Trial	5.8	1	300.2	23.1	54.1	1.8
2017	3.9	190	198.5	19.1	54.3	1.8
2018	4.1	171	221.4	18.7	54.4	1.7
2019	4.0	367	225.8	17.8	54.7	1.7
(1986-2021)	4.0	223	212.4	17.9	51.9	1.8

[a] ET_o = reference evapotranspiration, CP = cumulative precipitation, SR = solar radiation, Ta = mean air temperature, RH = relative humidity, WS = wind speed.

system included four quarter-circle, 102 mm (4-inch) tall pop-up sprinkler heads (Toro O-T-12-QP) within each plot. These sprinkler heads had an operating pressure range of 276-517 kPa (40-75 psi) and a flow rate range of 0.001-0.545 m^3 h-^{1} (0.06-2.4 GPM). To regulate the flow and maintain consistent water pressure, the sprinklers were equipped with a factory-installed, pressure-compensating disc (Toro Co., Bloomington, MN). Furthermore, an inline pressure regulator was installed upstream of the irrigation plots to regulate the pressure to approximately 380 kPa (55 psi).

A Weathermatic Smartline (SL) 4800 weather-based smart irrigation controller, connected to an SLW5 weather sensor, was utilized for autonomous irrigation scheduling (Telsco Industries, Inc., Garland, TX, USA). The controller employed the Hargreaves-Samani (HS) equation (Hargreaves & Samani, 1985) to calculate the reference evapotranspiration (ET_o) based on air temperature measurements at the site and estimations of extraterrestrial solar radiation based on latitude. Throughout the study, the controller automatically determined and implemented the irrigation treatments based on the programmed "plant type" and irrigation frequency data provided by the research team. Using the ET_o data and user-defined "plant type" values, the controller calculated the irrigation applications for each treatment (irrigation application = plant type × ET_o). These irrigation application values were then converted to irrigation runtime by the controller, taking into account the programmed precipitation rate for the irrigation system as set by the research team. The controller was configured to irrigate all treatment replications simultaneously. To monitor water usage and detect any leaks, an SLFSI-T10 Weathermatic flow sensor (Telsco Industries, Inc., Garland, TX, USA) was connected to the controller in 2017 and 2018, and a Badger Meter Recordall Turbo flowmeter (Badger Meter, Inc., Milwaukee, WI, USA) was used in 2019. Irrigation was scheduled between midnight and early morning to minimize water loss due to evaporation. The smart controller implemented a

run/soak schedule, ensuring sufficient soak time and reducing runoff after each irrigation application.

Table 2 presents a summary of the irrigation treatments used in the study. The experiment included 12 treatments, consisting of six irrigation levels and two irrigation frequencies, which were replicated three times. A factorial randomized complete block design with repeated measures over time was employed. The plots were established with sod in May 2017 and were under non-limiting irrigation to support root development and grass establishment for several months. The trials started on 9 July, 1 May, and 1 June in 2017, 2018, and 2019, respectively. The trials concluded on 5 October, 22 September, and 7 October in 2017, 2018, and 2019, respectively. After the trials were completed each year, non-limiting irrigation was applied to all plots for recovery. Standard cultural practices were followed to maintain the plots throughout the experimental periods. A triplex mower was used to mow the tall fescue plots to a height of approximately 45 mm, twice a week. Fertilizer was uniformly applied to all plots, and herbicides were regularly sprayed in the alleyways to control weed growth.

To assess the precipitation rate and distribution uniformity of the landscape sprinkler irrigation system, catch-can tests were conducted as per industry practice. Two tests were performed in 2017 and 2018 using catch-can devices. Each test had a duration of 10 minutes when the wind speed was below 2 m s^{-1}. In 2017, the test was repeated four times using 120 catch devices, while in 2018, it was repeated three times using 60 catch devices. The estimated low half distribution uniformity (DUlh) and precipitation rate of the irrigation system were 0.77 and 25 mm h^{-1} in 2017, and 0.81 and 22 mm h^{-1} in 2018. The DUlh was considered the irrigation efficiency in 2017 and 2018. In 2019, the precipitation rate of the system was set to 29 mm h^{-1} using the factory-calibrated Badger flow meter data. The irrigation efficiency was set to 0.76, calculated as the average flow measured by the flow meter divided by the flow estimated based on the 2018 catch-can test. The irrigation treatments ranged from 50% to 100% in 2017. Based on the response of the tall fescue to the irrigation treatments in 2017, the irrigation treatments were adjusted in 2018, ranging from 55%-80% ET_o, and kept the same in 2019 to ensure adequate replication of the treatments over time. The programmed irrigation levels ("plant type") in the smart controllers were equal to treatment ET_o levels divided by the irrigation efficiency. In 2017, the programmed irrigation levels varied from 65% to 130% of ET_o in 2017, between 68% and 99% of ET_o in 2018, and from 72% to 105% of ET_o in 2019. The irrigation frequencies (i.e., maximum allowed watering days per week) of three days per week (d wk^{-1}), 5 d wk^{-1}, and "on-demand" were replicated twice throughout the study. The "on-demand" treatment allowed the controller to regulate the irrigation frequency based on the actual ET_o demand. The controller was programmed with a default deficit threshold of approximately 4 mm to avoid light irrigation applications. This means that irrigation would only occur once a deficit of 4 mm had accumulated.

Table 2. Irrigation treatments and programmed irrigation levels.[a]

Irrigation	ET_o (%)						3 d wk^{-1}	5 d wk^{-1}	On-demand
Treatment-2017	50	60	70	80	90	100	✓	✓	
Treatment-2018	55	60	65	70	75	80	✓		✓
Treatment-2019	55	60	65	70	75	80		✓	✓
Programmed-2017	65	78	91	104	117	130	✓	✓	
Programmed-2018	68	74	80	86	93	99	✓		✓
Programmed-2019	72	79	86	92	99	105		✓	✓

[a] Programmed irrigation levels ("plant types") are equal to treatment levels divided by the irrigation efficiency in each year. The irrigation efficiency was set to 0.77, 0.81, and 0.76 in 2017, 2018, and 2019.

Data Collection & Statistical Analysis

NDVI & VR

The response of turfgrass to the irrigation treatments was assessed using two metrics: NDVI (Normalized Difference Vegetation Index) and VR (Visual Rating). Mean NDVI values were measured using the GreenSeeker handheld sensor (Trimble Inc., Sunnyvale, CA, USA), which has a measurement range of 0 to 0.99. Higher NDVI values indicate healthier and greener turfgrass. The measurements were conducted within two hours of solar noon and under cloud-free conditions from the center of each plot (~ 3–4m^2) to minimize edge effects. A visual rating of the plots was performed by an experienced rater according to the standards set by the National Turfgrass Evaluation Program (NTEP) using a scale of 1 (brown or dead plot) to 9 (ideal turfgrass), with a minimum acceptable threshold of 6 for residential areas (Morris and Shearman, 1998). In 2017, NDVI data were collected 12 times between 6 July and 22 September, while visual ratings were done 3 times. In 2018, NDVI data were collected 18 times from 30 April to 10 September, and visual ratings were done 18 times. In 2019, NDVI data were collected 16 times from 1 June to 7 October, and visual ratings were done 12 times. Only the VR and NDVI data collected less than two days apart were used to establish a relationship between NDVI and VR and determine a minimum NDVI threshold for tall fescue in the region. Therefore, 2017 was excluded from this analysis because the data were collected on different dates more than two days apart. The coefficient of variation (CV) was calculated between treatment replications to assess the stability of the NDVI and VR values.

The statistical analysis of the NDVI and VR data was conducted using PROC GLIMMIX in SAS 9.4 software (SAS Institute Inc., Cary, NC, USA). Each year was analyzed independently due to variations in trial length, weather conditions, and actual applied water by the smart controller. The fixed effects included irrigation levels, irrigation frequencies, and the data collection date, while the random effects included the block and its interaction with irrigation levels and frequencies. The significance of treatment effects was determined at p-values <0.05. Graphs were created using the plotting software package Veusz 3.4 (Sanders, 2008).

Soil Tension

A total of 48 Irrometer Watermark 200SS soil moisture sensors (Irrometer Co., Riverside, CA) were installed at four depths (20, 33, 43, and 64 cm) at the center of 12 plots (one experimental block). The sensors were connected to Irrometer 900M data loggers to monitor the soil tension across the irrigation treatments every 30 minutes. The Watermark soil moisture sensors determine the soil tension based on electrical resistance measurements. The measurement range of the

sensors is from 0 to 239 kPa. The following linear calibration equation (R^2 = 0.84) was developed in the laboratory. The adjusted soil tension data were then analyzed to evaluate water uptake patterns under different irrigation treatments.

$$pF_{calibrated} = 1.1405 \times pF_{measured} - 0.477 \quad (1)$$

where $pF_{measured}$ is the natural log of the soil tension (cm of water) measured by the watermark sensors.

NDVI & VR Turfgrass Water Response Function

A multiple linear regression model with the interaction term was used to develop tall fescue TWRF. To create the model, a composite 3-year dataset was constructed, incorporating the mean NDVI values as the response variable and the applied irrigation levels (%ET_o) and atmospheric evaporative demand (cumulative ET_o in mm) as input variables. The SAS 9.4 REG, PLOT, and UNIVARIATE Procedures (SAS Institute Inc., Cary, NC, USA) were used to develop the regression models and run diagnostics. The accuracy of the TWRF was assessed using two metrics: the mean absolute error (MAE) and the correlation coefficient (r).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|E_i - M_i\right| \quad (2)$$

where M and E are measured and estimated NDVI values, and n is the total number of measured data points for the entire experiment (n = 552).

The TWRF was used to estimate the performance of tall fescue to different irrigation applications (60%-110% ET_o) for a six month period (1 May to 31 October) under three scenarios of minimum, mean, and maximum atmospheric evaporative demands. Long term (1986-2021) daily ET_o data from CIMIS station 44 was used to identify the minimum, mean, and maximum recorded daily ET_o for each day from 1 May to 31 October. The minimum evaporative demand scenario consisted of a hypothetical year in which the ET_o for each day was set to the minimum ET_o value recorded by the CIMIS 44 station for that specific day. The same procedure was used to construct hypothetical years with a mean and maximum evaporative demand.

Performance of the Smart ET-Based Controller

The actual irrigation frequency for all treatments was determined by analyzing the recorded runtime data from the controller and comparing it to the programmed frequency restrictions. This analysis aimed to assess whether the actual irrigation frequency adhered to the set limitations. In the case of the on-demand irrigation scenario, the variation in actual irrigation frequency over time was examined in relation to the CIMIS ET_o data. This analysis provided insights into how well the controller adjusted the watering days based on the atmospheric evaporative demand.

To evaluate the accuracy of the ET_o estimation by the Weathermatic controller, daily ET_o data from CIMIS weather station 44 were utilized. CIMIS ET_o is calculated using a revised version of the Pruitt-Doorenbos modified Penman equation, incorporating a unique cloud factor value for each station and a wind function developed at the University of California, Davis (Eching, 1998). The runtime irrigation values for all treatments were stored in the irrigation controller. These data were retrieved and used to calculate the actual applied irrigation amounts, considering the irrigation treatment, irrigation efficiency, and flowmeter-based irrigation precipitation rate values. To quantify the impact of non-standard surface conditions on ET_o estimation by the smart controller, we utilized the Hargreaves-Samani (HS) model to calculate ET_o using temperature data recorded by the smart controller, which represented non-standard surface conditions found in urban areas. We then compared these ET_o values with HS ET_o estimations based on CIMIS temperature data, which represented well-watered standard surface conditions. Additionally, long-term CIMIS ET_o data from station 44 were compared with the HS ET_o to evaluate the performance of the HS model for different seasons and years, including those characterized by extreme meteorological conditions.

Results

The catch can test is commonly employed to determine the precipitation rate of pop-up sprinkler heads. However, in our study, the estimated irrigation application rates obtained from the catch can tests (25 mm h^{-1} in 2017 and 22 mm h^{-1} in 2018) were lower than the measured application rate obtained from the calibrated flowmeter (29 mm h^{-1} in 2019). In the results and discussion sections, only the revised irrigation application rates (expressed as percentages of CIMIS-ET_o) are reported (table 3). These values were recalculated for all years using the irrigation run time values retrieved from the smart controller and assuming a precipitation rate of 29 mm h^{-1} for the irrigation system throughout the study.

Performance of the Irrigation Controller

The smart controller slightly overestimated ET_o in all years compared to CIMIS ET_o. In 2017, the mean overestimation was 14%, varying between 12%-17% across the treatments. In 2018, the mean overestimation was 2%, ranging from 1%-3% among the treatments. In 2019, the overestimation of ET_o on average was 2% and varied between 2%-4% across the treatments. In part, the higher relative error in 2017 was due to a connectivity issue between the wireless

Table 3. Irrigation treatments versus programmed and applied irrigation levels.[a]

Irrigation	ET_o (%)					
Treatment-2017	50	60	70	80	90	100
Programmed-2017	65	78	91	104	117	130
Applied by the Controller-2017	70	83	96	109	122	135
Treatment-2018	55	60	65	70	75	80
Programmed-2018	68	74	80	86	93	99
Applied by the Controller-2018	80	86	93	101	108	115
Treatment-2019	55	60	65	70	75	80
Programmed-2019	72	79	86	92	99	105
Applied by the Controller-2019	61	67	73	77	82	92

[a] Programmed irrigation levels ("plant types") are equal to treatment levels divided by the irrigation efficiency in each year. The irrigation efficiency was set to 0.77, 0.81, and 0.76 in 2017, 2018, and 2019. In 2017 and 2018, the precipitation rate of the irrigation system was calculated using early trial catch-can tests and set to 25 and 22 mm h^{-1}, respectively. In 2019, the precipitation rate was set to 29 mm h^{-1} based on flow data from a calibrated flowmeter. Consequently, the abovementioned applied irrigation levels for 2017 and 2018 were also recalculated using the 29 mm h^{-1} precipitation rate.

weather sensor and the controller at the beginning of the trial. A wired weather sensor was used in years 2 and 3 to avoid the same issue. Overall, the HS ET_o values were 2.3% higher when calculated using temperature data recorded by the smart controller weather sensor versus CIMIS temperature data.

Figure 2 shows the long-term (34 years) performance of the HS model against CIMIS ET_o. The r = 0.91 and MAE = 0.42 mm d^{-1} illustrated the high accuracy of the HS model for estimating ET_o, which was also evident from the well-scattered data points around the reference 1:1 line. The MAE values fluctuated between 0.1 and 0.3 mm d^{-1} for most of the years, indicating the consistent performance of the HS model (fig. 2b). The monthly error values were in the acceptable range in all seasons, yet relatively higher MAE values were observed in winter and spring than in summer (fig. 2b).

In 2017, the actual irrigation frequency varied between 3.8 and 4.7 d wk^{-1}, with a mean value of 4.3 d wk^{-1} for the 5 d wk^{-1} treatment. For the 3 d wk^{-1} treatment, the mean frequency was equal to 3 d wk^{-1}, and a slight variation was observed among the treatments, ranging from 3 to 3.1 d wk^{-1}. In 2018, for the 3 d wk^{-1} frequency, the actual frequency fluctuated between 2.9 and 3.3 d wk^{-1}, and the mean frequency was equal to 3 d wk^{-1}. For the on-demand irrigation treatment, the frequency varied between 5.5 and 6.6 d wk^{-1} across the treatments, with a mean value of 6.1 d wk^{-1}. In 2019, the irrigation frequency varied between 5.9 and 6.8 d wk^{-1}, with a mean frequency of 6.5 d wk^{-1} for the on-demand irrigation scenario. In 2018 and 2019, the irrigation frequency changed over time for the on-demand irrigation scenario. More frequent irrigation applications were made when ET_o demand was high, and the irrigation frequency decreased for periods when ET_o demand subsided. In 2019, for the 5 d wk^{-1} treatment, the mean frequency was 4.6 d wk^{-1} and the range was 4-4.9 d wk^{-1}. Overall, greater irrigation treatments caused more frequent irrigation applications in all three years.

Relationship Between NDVI & VR

Figure 3 represents the scatter plot of NDVI versus VR values for 2018 and 2019. The slope of the regression equations varied between years. The NDVI and VR data were highly correlated in both years, with R^2 = 0.81 in 2018 and R^2 = 0.79 in 2019. The R^2 for the composite dataset was equal to 0.77. The linear regression model between VR and NDVI data for the combined dataset showed the NDVI value of 0.7 as the minimum threshold to maintain acceptable tall fescue quality for residential areas.

Impact of Irrigation Treatment On Tall Fescue Growth and Health

NDVI

Table 4 summarizes the statistical analysis of NDVI and VR data for the tall fescue irrigation trial in 2017-2019. Figure 4 shows the NDVI dynamics across treatments over time in all three years. In 2017, the NDVI values ranged from 0.29 to 0.81. The difference between mean NDVI values for the maximum and minimum irrigation applications of 70% and 135% ET_o was 0.24. In 2017, the impact of irrigation rate was significant on NDVI values (p < 0.001). The highest NDVI values were associated with greater irrigation applications, as expected. However, the differences between the NDVI values for the top four irrigation treatments, ranging from 96%-135% ET_o, were not significant. The lowest two irrigation applications of 70% and 83% ET_o caused a significant decrease in NDVI values compared to the greater irrigation treatments. The top three irrigation application levels (109%, 122%, and 135% ET_o) stayed above the minimum NDVI threshold of 0.7 for the entire experimental period. The 96% ET_o treatment showed some decline toward the end of the trial to NDVI values below the minimum threshold. The lowest two irrigation treatments (70% ET_o and 83% ET_o) only maintained the turfgrass quality for roughly one month and showed a gradual decline to NDVI values around 0.4. The impact of irrigation frequency restriction scenarios (3 d wk^{-1} versus 5 d wk^{-1}) was significant on NDVI (p < 0.05), and higher NDVI was associated with more frequent irrigation applications. Overall, the fluctuations in NDVI values of irrigation treatments over time were similar for the 3 d wk^{-1} and 5 d wk^{-1} treatments, except that the lower irrigation treatments showed an earlier decline in NDVI values for the 3 d wk^{-1} than the 5 d wk^{-1} frequency.

In 2018, the NDVI values ranged from 0.41 to 0.83. The highest mean NDVI value was 0.8 (115% ET_o), and the lowest mean NDVI value was 0.64 (80% ET_o). In 2018, the impact of irrigation levels (p <0.001) and frequency (p <0.01) was significant on NDVI values. Higher irrigation applications were associated with higher NDVI values, as expected.

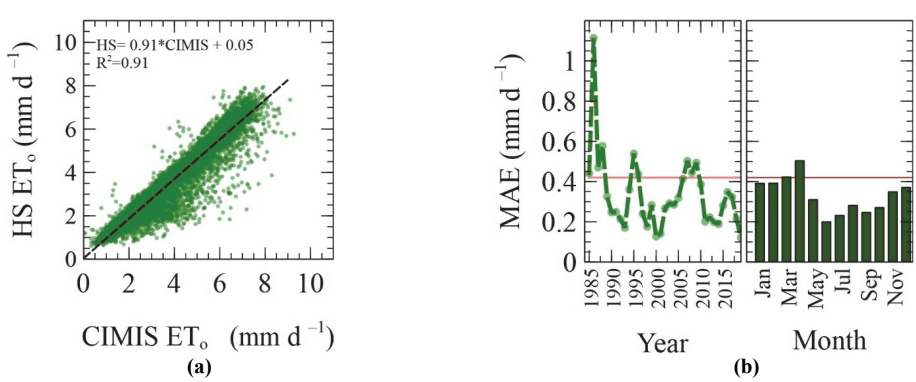

Figure 2. Long-term performance of the Hargreaves and Samani (HS) model compared to CIMIS ET_o for the experimental area; (a) scatter plot of the HS ET_o versus CIMIS ET_o and (b) variation in annual and seasonal mean absolute error (MAE) values based on the difference between the HS and CIMIS models. The red horizontal line in figure b represents the mean MAE value.

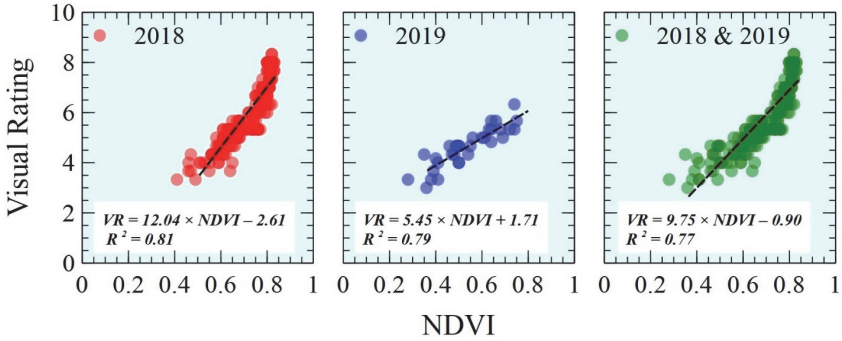

Figure 3. Relationship between visual rating (VR) and NDVI data collected in 2018 and 2019 for tall fescue under varying irrigation treatments at UCR agricultural experiment station in Riverside, CA.

Table 4. Statistical analysis of the tall fescue response in terms of visual rating and NDVI to irrigation treatments in 2017, 2018, and 2019.

2017			2018			2019		
ET_o%[a]	NDVI	VR	ET_o%	NDVI	VR	ET_o%[b]	NDVI	VR
70%	0.54 b	4.1 c	80%	0.64 c	5.2 e	61%	0.49 c	4.2 b
83%	0.56 b	4.4 c	86%	0.70 bc	5.7 cd	67%	0.54 bc	4.5 b
96%	0.71 a	5.7 b	93%	0.68 c	5.5 de	73%	0.58 ab	4.6 b
109%	0.76 a	6.8 a	101%	0.75 ab	6.0 bc	77%	0.62 a	5.2 a
122%	0.76 a	6.9 a	108%	0.76 ab	6.4 b	82%	0.62 a	5.2 a
135%	0.78 a	7.3 a	115%	0.80 a	6.9 a	92%	0.66 a	5.4 a
Days	NDVI	VR	Days	NDVI	VR	Days	NDVI	VR
3 d w^{-1}	0.66 b	5.6 b	3 d w^{-1}	0.69 b	5.7 b	5 d w^{-1}	0.57 a	4.7 a
5 d w^{-1}	0.71 a	6.2 a	7 d w^{-1}	0.75 a	6.2 a	7 d w^{-1}	0.56 a	4.7 a
P-value[c]			*P*-value			*P*-value		
I	***	***	I	***	***	I	**	**
F	*	*	F	**	**	F	NS	NS
I×F	NS	NS	I×F	NS	NS	I×F	NS	NS
T	***	***	T	***	***	T	***	***
I×T	***	**	I×T	***	***	I×T	***	NS
F×T	***	NS	F×T	***	***	F×T	NS	NS
I×F×T	***	*	I×F×T	NS	NS	I×F×T	NS	NS

[a] The irrigation levels were adjusted based on the actual water application calculated using the calibrated flow meter data in 2019. I, F, and T in the table refer to irrigation levels, irrigation frequency, and time (i.e., repeated measures of NDVI and VR each year over time), respectively.

[b] In 2019, two irrigation treatments (77% and 82% ET_o for the 5 d wk^{-1} frequency) were programmed incorrectly. Therefore, the letter assignments for irrigation frequency were based on standard error obtained from analyzing the remaining four irrigation treatments.

[c] NS, ***, ** and * are non-significant or significant at p <0.001, 0.01, and 0.05, respectively. Means sharing a similar letter are not significantly different, based on Turkey's Test at $\alpha = 0.05$.

The NDVI values among the top three irrigation treatments, varying between 101% and 115% ET_o, were not significantly different. The lowest three irrigation applications (80%, 86%, and 93% ET_o) had statistically similar NDVI values that were significantly different than the NDVI value for the maximum irrigation application of 115% ET_o. The on-demand irrigation scenario resulted in significantly higher NDVI than the 3 d wk^{-1} irrigation frequency (p < 0.01). Overall, the 3 d wk^{-1} frequency restriction caused lower NDVI values than the on-demand irrigation scenario, particularly for the lesser irrigation treatments (fig. 4). The top three irrigation treatments (101%, 108%, and 115% ET_o) stayed above NDVI of 0.7 during the trial for the on-demand frequency and stayed above 0.6 for the 3 d wk^{-1} frequency. For the on-demand frequency, the lesser three treatments (80%, 86%, and 93% ET_o) maintained the quality above NDVI of 0.7 for roughly 1.5 months and then showed a decline to NDVI values close to 0.6, which was stabilized until the end of the trial. The 3 d wk^{-1} frequency, on the other hand, caused a more pronounced decline in NDVI values to 0.4-0.5 range for the 80% and 93% ET_o treatments after approximately one month.

Analysis of the irrigation application data at the end of the trial revealed that two irrigation treatments were programmed incorrectly in 2019 for the 5 d wk^{-1} frequency. The actual irrigation application for those two treatments were 56% (instead of 77%) and 61% (instead of 82%) ET_o. Therefore, the letter assignments for irrigation frequency in table 4 were based on the standard error obtained from analyzing the remaining four irrigation treatments. In figure 4, the actual irrigation applications for all the treatments are shown, including the incorrectly programmed treatments. In 2019, the impact of irrigation level was significant (p < 0.01), but the impact of irrigation frequency was not significant on NDVI values. Irrigation applications in 2019 were substantially lower than the previous years, which resulted in lower NDVI values across the treatments, ranging from 0.27 to 0.80. No treatments kept the NDVI values above the minimum threshold. The highest mean NDVI value of 0.66 was due to 92% ET_o, and the lowest mean NDVI value of 0.49 was due to 61% ET_o irrigation application. The NDVI decreased with the decline in the irrigation applications, but the differences were not significant for the highest four irrigation applications, ranging from 73% to 92% ET_o. Relatively lower irrigation applications in 2019 compared to the previous years

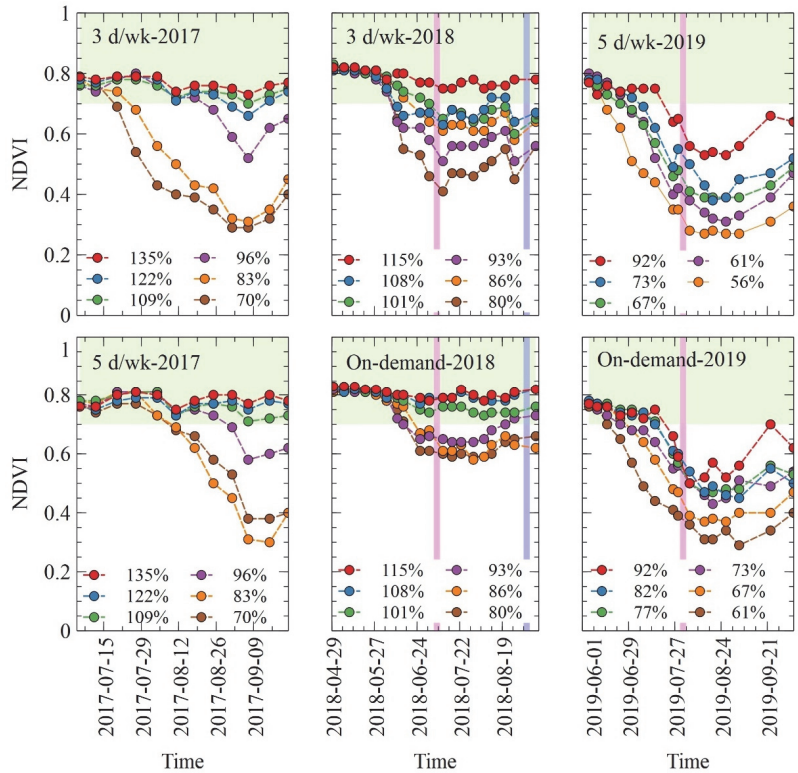

Figure 4. The tall fescue turfgrass response (NDVI values) to varying irrigation treatments in 2017, 2018, and 2019. The cumulative ET_o in 2017, 2018, and 2019 trial periods were 378 mm, 777 mm, and 741 mm, respectively. The pink and purple strips mark the dates when the cumulative ET_o passed 378 and 741 mm, respectively. NDVI values greater than 0.7 are highlighted in green to show the accepted quality range for residential areas.

caused a more rapid decline in NDVI values during the trial. The greatest irrigation level of 92% ET_o maintained the NDVI values above the minimum threshold for 1.5 months and then showed a gradual decline to NDVI close to 0.6 and finally some recovery toward the end of the trial. All the treatments showed some recovery and gradual increase in NDVI values toward the end of the trial; however, that was not enough to bring the quality up to the minimum acceptable threshold. A greater and quicker decline in NDVI values down to the 0.2-0.4 range happened for more severe deficit irrigation treatments of less than 70% ET_o. The NDVI fluctuations across the treatments were similar for the 5 d wk^{-1} frequency and on-demand irrigation scenario.

Visual Rating

Table 4 summarizes the statistical analysis of VR values for the three years of the tall fescue irrigation trial. Figure 5 illustrates the VR variability over time for all the treatments from 2017 to 2019. In 2017, the VR values ranged from 2 to 9 across the treatments. The highest mean VR value of 7.3 and the lowest mean VR value of 4.1 were due to the maximum (135% ET_o) and minimum (70% ET_o) irrigation applications. The impacts of irrigation levels ($p < 0.001$) and frequencies ($p < 0.05$) on VR values were significant. The differences in VR values (7.3-6.8) among the top three irrigation applications (135%-109% ET_o) were not significant. The lowest two irrigation treatments (70% and 83% ET_o) had significantly lower VR values than the other treatments. A more restrictive irrigation frequency of 3 d wk^{-1} statistically decreased the VR values compared to a 5 d wk-1 frequency. The VR for the top three treatments (109%, 122%, and 135% ET_o) stayed above or very close to the minimum threshold, despite an overall decline over time (fig. 5). The fluctuations in VR values over time were similar for both frequency restrictions (3 d wk^{-1} and 5 d wk^{-1}), yet the 5 d wk^{-1} frequency yielded slightly higher VR values for some treatments.

In 2018, the VR values varied between 3 and 8.3 across the irrigation treatments. The impacts of irrigation level ($p < 0.001$) and frequency ($p < 0.01$) were significant on VR values. The maximum and minimum mean VR values of 6.9 and 5.2 were due to the greatest and lowest irrigation applications of 115% and 80% ET_o, respectively. The top irrigation application of 115% ET_o resulted in a statistically higher VR value than other treatments. In 2018, the top two irrigation levels of 108% and 115% ET_o stayed above the minimum threshold for the on-demand irrigation scenario. Other treatments stayed over the minimum threshold for roughly 1.5-2 months with a gradual decline until they reached values in the 4-6 range and stayed stable with minimum fluctuations. The trends were similar for the 3 d wk^{-1} frequency, yet the VR values were lower than the on-demand scenario.

The VR values ranged from 2.8 to 7 across the treatments in 2019. The highest VR value of 5.4 and the lowest VR of 4.2 were due to the maximum and minimum irrigation applications of 92% and 61% ET_o, respectively. The impact of irrigation levels was significant ($p < 0.01$), but irrigation frequency showed no significant effect on VR values. The top three irrigation applications ranging from 77% to 92% ET_o had similar VR values, which were significantly higher than

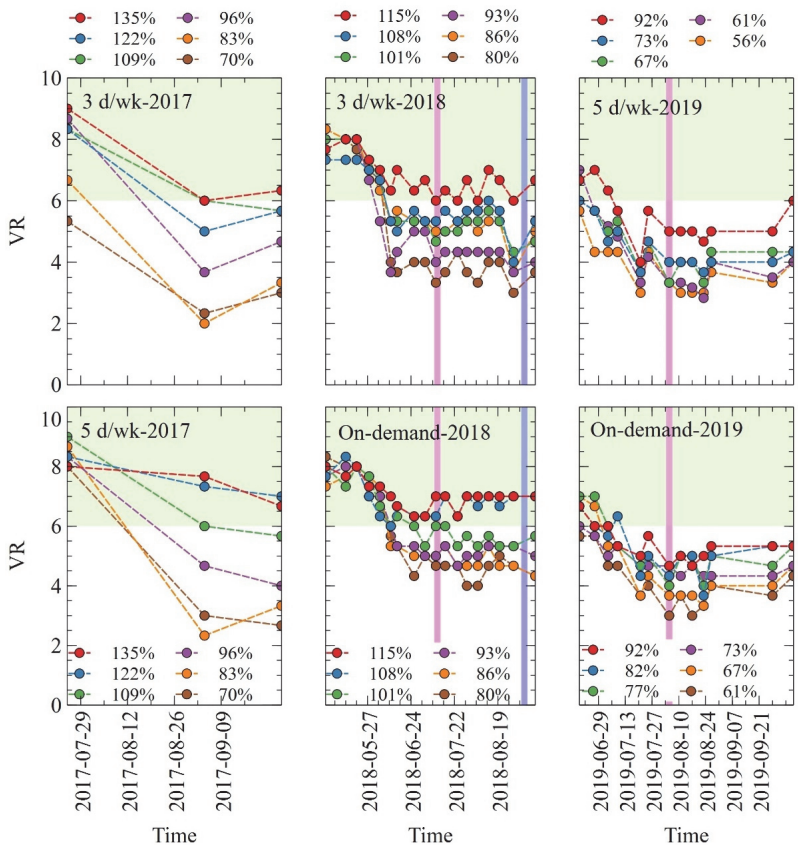

Figure 5. Changes in visual rating (VR) values over time across the irrigation treatments in 2017, 2018, and 2019. The cumulative ET_o in the 2017, 2018, and 2019 trial periods were 378 mm, 777 mm, and 741 mm, respectively. The pink and purple strips mark the dates when the cumulative ET_o passed 378 and 741 mm, respectively. VR values above six are highlighted in green to show the accepted quality range for residential areas.

the remaining treatments. The difference among the VR values of the lowest three irrigation applications (61%, 67%, and 73% ET_o) was not significant. The VR values decreased sharply and dropped below the minimum acceptable threshold very soon and no treatment maintained an acceptable quality throughout the trial. After 1.5-2 months, the VR values reached a 3-5 range for most treatments, with minimal changes until the end of the experiment.

Soil Tension

The soil moisture fluctuations under different irrigation treatments in 2017 are shown in figure 6. The maximum irrigation application of 135% ET_o and 5 d wk^{-1} frequency kept the soil moisture fluctuation minimal and lower than 50 kPa at all depths during the trial. The deepest sensor (64 cm) showed minimal fluctuations, and soil tension stayed below 50 kPa for all the treatments. The shallow sensors (20 and 33 cm) showed soil moisture depletion over time, similar across the treatments, which happened faster for lesser irrigation levels. The readings of the 43 cm deep sensor showed a decline for the lowest irrigation levels of 70%, 83%, and 96% ET_o, which was more pronounced for the 5 d wk^{-1} frequency. For the top three irrigation levels (135%, 122%, and 109% ET_o), most of the 43 cm deep sensors showed minimal fluctuations. The soil tension showed root water uptake in 8 out of 12 plots down to 43 cm.

Figure 7 shows the soil moisture fluctuations under different irrigation treatments in 2018. In all the treatments (except 108% ET_o at 3d wk^{-1}), the deepest sensor showed no or slight fluctuation in soil tension. The top three sensors showed soil moisture depletion in most treatments as time progressed. For treatments less than 100% ET_o, the top two sensors showed a rapid increase in soil tension up to 239 kPa (the maximum possible reading by the sensors) in less than two months with no significant profile refilling due to irrigation applications. The 115% ET_o and 108% ET_o treatments with on-demand frequency showed an overall decline in soil moisture in the top three sensors, but fluctuations in soil tension indicated partial soil profile refilling due to irrigation applications. The 43 cm deep sensor showed soil moisture depletion patterns, indicating root water uptake in two-thirds of the plots.

Figure 8 shows the soil tension data across the irrigation treatments in the 2019 experimental season. The deepest sensor at 64 cm showed little to no fluctuations in most treatments (except for 67% ET_o with on-demand frequency and 56% ET_o with 5 d wk^{-1} frequency). The top two sensors showed a rapid decline in soil moisture to soil tension values close to 200-239 kPa for almost all treatments except for the 33 cm-deep sensor that declined to 150 kPa under 67% ET_o treatment with 5 d wk^{-1} frequency. In most plots (9 out of 12), the 43 cm sensor showed a decline in soil moisture as the season progressed.

Turfgrass Water Response Function

Figures 9a and 9b show the performance of the TWRF (eq. 3) developed for tall fescue using the experimental data collected in 2017-2019 to estimate NDVI using irrigation

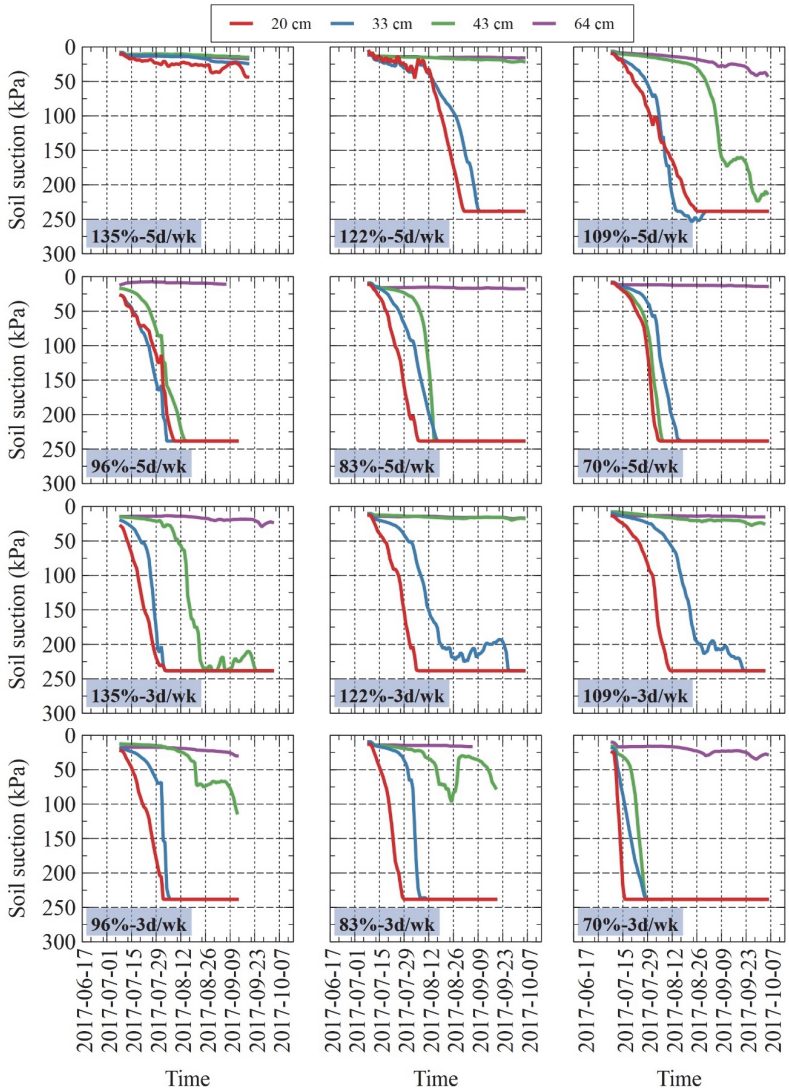

Figure 6. The dynamic of soil tension data (kPa) over time in 2017 across the irrigation treatments at four depths (20, 33, 43, and 64 cm).

application (I, percentages of ET_o) and atmospheric evaporative demand (CET, cumulative ET_o, mm).

$$NDVI = 0.69 - 0.14\times10^{-2}(CET) + 0.07(I) + 0.12\times10^{-2}(CET)(I) \quad (3)$$

MAE = 0.06 and r = 0.82 indicated an acceptable fit for the linear TWRF. Figure 9c shows the NDVI estimated based on long-term ET_o (1986-2019) data for three scenarios of maximum, mean, and minimum ET_o values and six irrigation applications ranging from 60%-110% ET_o. The cumulative ET_o was 382 mm, 944 mm, and 1329 mm for scenarios with the minimum, mean, and maximum evaporative demands, respectively. The estimations were done for six months, from 1 May to 31 October. The 110% ET_o application kept the NDVI above the minimum threshold for the entire simulation period for all three atmospheric conditions. Under maximum evaporative demand, the 100% ET_o treatment maintained the quality for 50 days, and a gradual decline in NDVI eventually reached a minimum value of 0.52. The differences between NDVI values for the scenarios with minimum and maximum evaporative demands were more pronounced for lower irrigation applications. For instance, the lowest irrigation application of 60% ET_o kept the NDVI above the threshold for 7 and 43 days under the maximum and minimum evaporative demand scenarios, respectively.

Discussion

Autonomous Irrigation Management Using Weathermatic Smart Controller

Reliability of ET_o Estimation

Overestimation of the ET_o by the smart controller was minimal (2%) in 2018 and 2019 and slightly higher (14%) in 2017. Our long-term evaluation of the performance of the HS model showed its high accuracy in summer, indicating that the smart irrigation controllers that estimate ET_o based on the HS model could be used for efficient autonomous irrigation scheduling. However, adequate landscape irrigation scheduling using these controllers also depends on the availability of science-based plant factor information for other

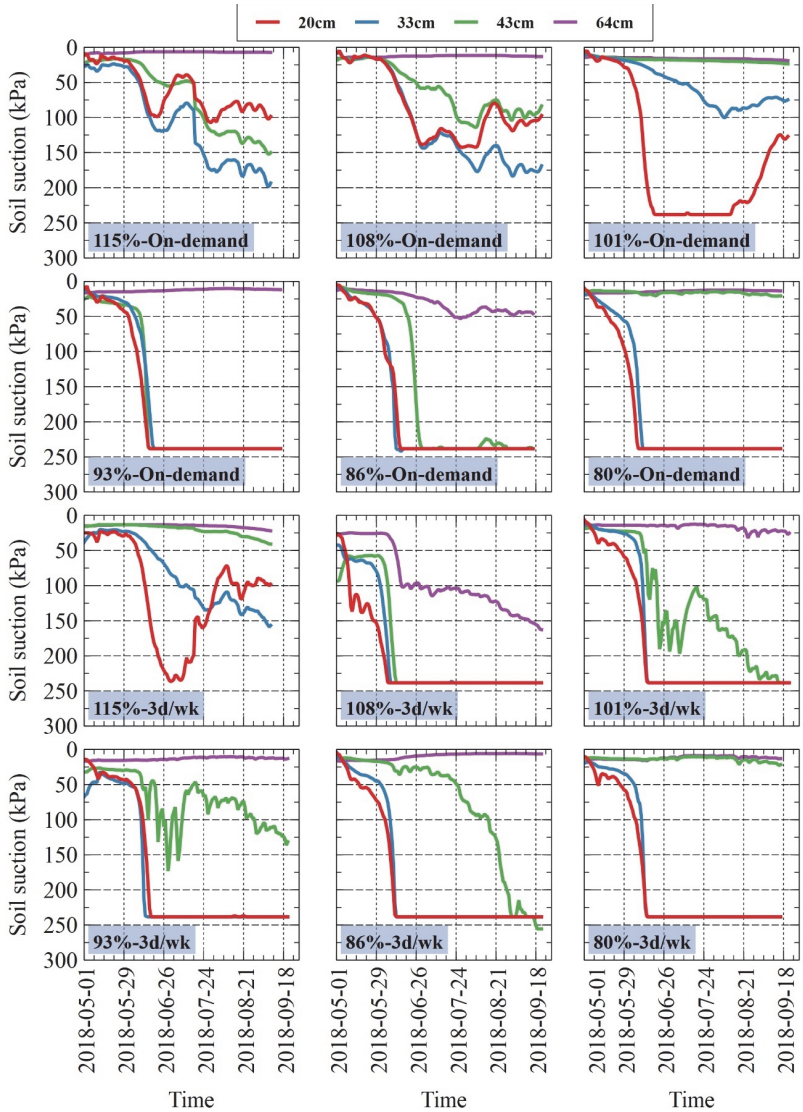

Figure 7. The dynamic of soil tension data (kPa) over time in 2018 across the irrigation treatments at four depths (20, 33, 43, and 64 cm).

alternative landscape species to maintain acceptable quality with minimum water application.

Theoretically, weather data should be collected above the well-watered standard reference crop to calculate the ET_o. However, the weather sensors of the smart ET-based controllers may be installed over non-standard surface conditions in urban areas. (Alexandris and Proutsos, 2020) showed that collecting data over bare ground causes an overestimation of the ET_o by the HS model, given the higher air temperature compared to the well-watered standard surfaces. In our study, the Weathermatic weather sensor was installed at the edge of the research site, surrounded by the road (bare soil) and irrigated turfgrass plots under different irrigation treatments. However, a higher maximum air temperature only caused a 2.3% difference in HS ET_o values calculated using temperature data recorded by the smart controller weather sensor versus CIMIS temperature data. These results suggest that the overestimation of the ET_o by the smart controller due to non-standard surface conditions could be negligible for urban landscape irrigation when an on-site weather sensor is installed close to the irrigated landscape. Further research is needed to quantify the impact of non-standard surface conditions on ET_o estimations by the smart controllers across typical land-use and land-cover combinations in urban areas.

On-Demand Irrigation Versus Irrigation Frequency Restriction

Water agencies and municipalities in California often implement irrigation restrictions during droughts, limiting watering days to specific days per week in order to reduce urban irrigation. Less frequent irrigation is commonly believed to promote deep rooting and improve turfgrass quality, enabling it to withstand environmental stress. A field study conducted in Texas by Jordan et al., (2003) demonstrated that reducing irrigation frequency from every 1 or 2 days to every 4 days resulted in a deeper bentgrass root system and improved overall health and quality. Contrary to these findings, our results indicated that limiting irrigation frequency to 3 days per week did not contribute to water conservation or enhance VR and NDVI of tall fescue compared to the 5 d wk^{-1} and on-demand irrigation treatments. Additionally, our adjacent hybrid bermudagrass trial (Haghverdi et al., 2021c)

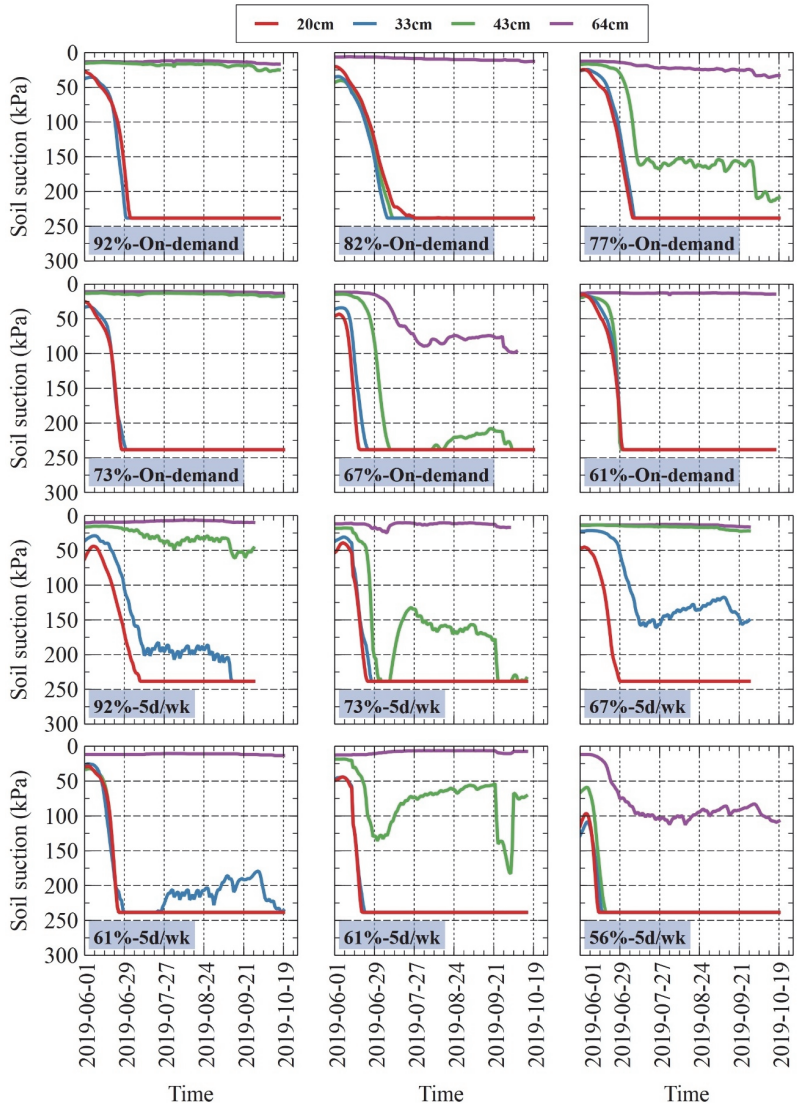

Figure 8. The dynamic of soil tension data (kPa) over time in 2019 across the irrigation treatments at four depths (20, 33, 43, and 64 cm). Duplication of 61% ET_o treatment (5 d wk^{-1}) was due to the smart controller programming issue.

did not show significant water savings or turfgrass quality improvements associated with restricting irrigation frequency. In our study, the on-demand irrigation scenario implemented with the Weathermatic smart controller allowed for dynamic adjustment of irrigation frequency based on the actual ET demand over time. More frequent irrigation applications were made during periods of high atmospheric evaporative demand, while the irrigation frequency decreased during periods of reduced demand. This approach improved turfgrass VR and NDVI values compared to limiting irrigation frequency. Therefore, we recommend implementing on-demand irrigation frequency in similar semi-arid regions during the summer, particularly when controllers have settings to avoid light irrigation applications.

Sustaining the Quality of Tall Fescue

An average crop coefficient of 0.95 was reported for tall fescue in a recently published review paper focusing on cool-season turfgrass water use and requirements (Braun et al., 2022a). Overall, tall fescue crop (ET_c) was found to be approximately 20% higher than the general weighted ET_c across all cool-season species. Additionally, significant variation in water requirements was reported under non-limiting soil moisture conditions (up to 15%) for both low and high ET cultivars, along with a wide range of drought resistance among tall fescue cultivars (Braun et al., 2022b). Consequently, it is essential to investigate various cultivars and species of turfgrass to understand their water usage and drought tolerance under different climate conditions. Studies conducted in the southwestern USA in California (Richie et al., 2002), Nevada (Brown et al., 2004), and Colorado (Ervin and Koski, 1998) suggest irrigation applications between 75%-85% ET_o to maintain the color and coverage of tall fescue turfgrass at an acceptable condition. However, our results showed that irrigation application rates less than 100% ET_o were insufficient to maintain the quality of tall fescue during the trial periods. Irrigation application rates between 80% and 90% ET_o only maintained the turfgrass quality above the minimum thresholds for 1-2 months. In a separate study, we observed that irrigation application at 108% of the ET_o level kept the VR values within an acceptable range

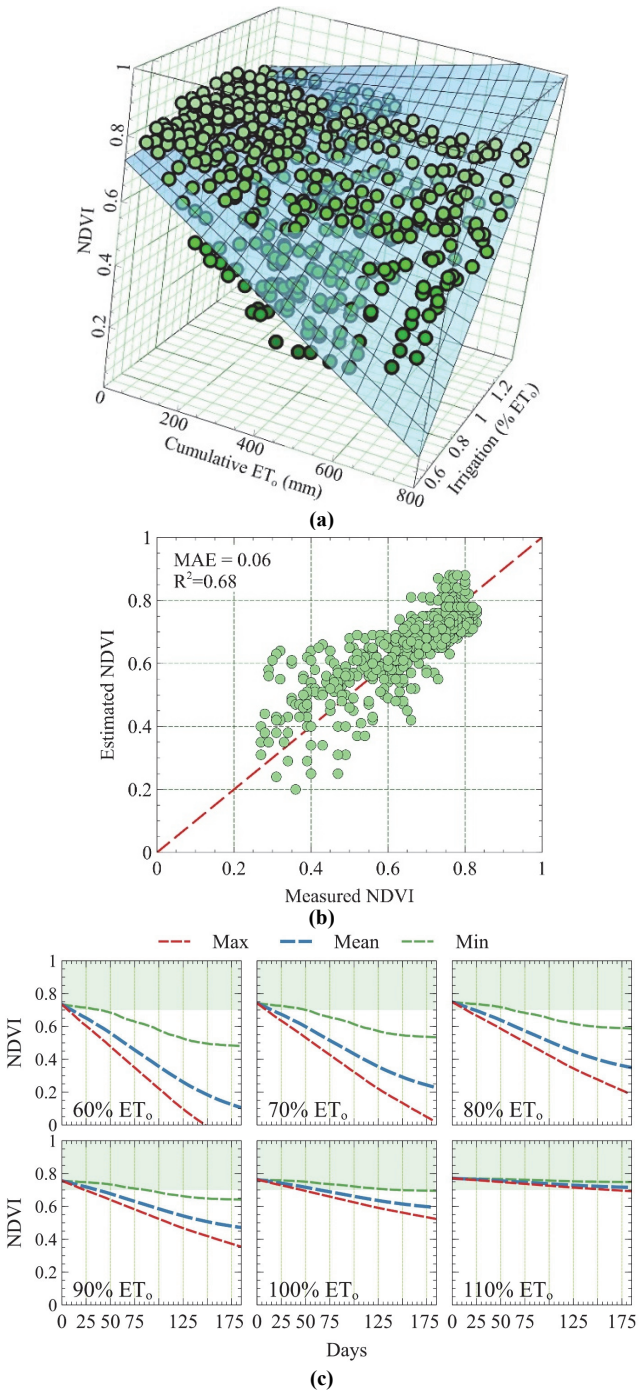

Figure 9. (a) The response of tall fescue to applied irrigation levels (% ET_o) over time. Blue surface: fitted TWRF; green circles: measured data. (b) Measured versus TWRF-estimated NDVI values. (c) Estimated response of tall fescue to varying irrigation scenarios (1 May to 31 October) using TWRF based on the minimum (382 mm), mean (944 mm), and maximum (1329 mm) atmospheric evaporative demands.

(except for a brief period) for tall fescue (a blend of 'PennRK4', 'Rebel XLR', + 'Firecracker SLS') in central California (Haghverdi et al., 2021a). Similar results were reported by Serena et al. (2020), who used the Irritrol Climate Logic Weather Sensor for irrigation management of 'Advantage' tall fescue in Las Cruces, NM, USA. Their controller applied 119% and 132% ET_o in spring and summer 2013, which kept the visual quality rating above the minimum threshold. In their study, irrigation application of 81% ET_o and 61% ET_o in Fall 2013 and Winter 2014 caused a decline in visual quality that eventually led to ratings below the minimum threshold in spring 2014, despite 117% ET_o application by the controller. The applied irrigation by the smart controller in our study was the sum of water used by turfgrass and inevitable water losses by pop-up sprinkler heads due to evaporation, wind drift, and runoff. Therefore, switching to irrigation methods that reduce water loss, such as subsurface drip irrigation, is expected to help maintain the tall fescue quality with lower irrigation application rates than the values reported in this study. In our recently published study, we showed that drought-tolerant groundcover species such as *Rhadogia spinescens*, *Baccharis* × 'Starn' Thompson, and *Eriogonum fasciculatum*' Warriner Lytle' maintained their growth and visual quality at 24% ET_o irrigation applied autonomously using the Weathermatic smart irrigation controller in inland southern California (Sapkota et al., 2023). Hence, adopting alternative groundcovers and drought-tolerant turfgrass species (when wear tolerance for human or animal use is not essential) represents the most effective strategy for conserving water.

The TWRF estimations showed that 60% ET_o application held the turfgrass quality above the minimum threshold for 7 and 43 days, depending on the atmospheric evaporative demand. A study conducted in the humid environment of eastern Kansas in a Chase silty clay loam showed that 50% ET_o irrigation applications maintained tall fescue quality above the minimum threshold for 45-82 days (Hong et al., 2021). The TWRF estimations suggested that 110% ET_o would be sufficient to maintain the tall fescue quality above the minimum threshold even under extremely high atmospheric evaporative demand. This is substantially higher than the 75% ET_o demand for hybrid bermudagrass based on TWRFs developed in our earlier study conducted in an adjacent site (Haghverdi et al., 2021c). The results also revealed that higher atmospheric evaporative demand has a more pronounced deteriorating impact on tall fescue growth and health when more severe deficit irrigation scenarios are implemented.

A field study conducted in Kansas revealed that, under well-watered conditions and silt loam soil, approximately 86% of the tall fescue's root length was concentrated in the upper 30 cm of soil (Su et al., 2008). In our study, the soil moisture sensors displayed fluctuations down to a depth of 43 cm, while the deepest sensor at 64 cm only detected changes in soil tension for a limited number of plots. Furthermore, the soil moisture sensors indicated that less frequent irrigation often reached deeper layers, as anticipated, but did not result in improved turfgrass quality compared to on-demand irrigation by the smart controller. These findings suggest that the primary water uptake activities of the roots were restricted to the topsoil layer in our coarse sandy loam soil. The two top sensors (20 cm and 33 cm), in most cases, exhibited a gradual decline over time and were never completely replenished, indicating that the applied irrigation water primarily replenished the shallow soil layer (<20 cm). Overall, establishing a direct relationship between NDVI and VR data and the soil moisture patterns for all the treatments proved to be challenging. The variations in soil

tension over time were sometimes similar among treatments, despite significant differences in VR and NDVI values.

NDVI AND VR OF TALL FESCUE

Our study found a high correlation (r = 0.88) between the NDVI and VR data for the combined 2018 and 2019 data. This is slightly higher than the r = 0.75 reported for tall fescue in Manhattan, Kansas (Bremer et al., 2011a). In their study near Manhattan, KS, Hong et al. (2019) reported a correlation coefficient ranging from 0.87 to 0.90 between handheld-based NDVI and visual quality ratings of creeping bentgrass (*Agrostis stolonifera* L.). On the other hand, Leinauer et al. (2014), using a comprehensive dataset, found correlation coefficients of 0.71 (for 113 tall fescue varieties irrigated with potable water) and 0.73 (for 114 tall fescue varieties irrigated with saline water) between VR and NDVI in Las Cruces, NM.

Using the fitted linear regression model, we determined the NDVI value of 0.7 as the minimum threshold to maintain the tall fescue's quality acceptable for residential areas. This slightly exceeds the threshold of 0.6 to 0.65 for tall fescue (a blend of 'PennRK4,' 'Rebel XLR,' and 'Firecracker SLS') as determined in our recently conducted study in central California (Haghverdi et al., 2021b). We conducted an adjacent hybrid bermudagrass trial in southern California that showed an NDVI of 0.6 as the minimum acceptable quality for residential areas (Haghverdi et al., 2021c). Therefore, these thresholds should be identified separately for each turfgrass species, cultivar, and respective region. The slope and intercept of fitted regression lines in our study differed between years, which was also reported by Bremer et al. (2011a). This season-to-season variability could be a potential practical limitation in developing a universal equation for estimating VR based on NDVI data.

Variation in NDVI and VR values between treatment replications is expected to be minimal, which was the case in 2018 and 2019, indicating consistency in both NDVI and VR data. In 2017, however, a 73% higher CV was observed for VR data compared to NDVI data collected from the closet dates. This could be attributed to NDVI being a more stable and repeatable parameter than VR to assess the overall quality and health of tall fescue turfgrass. More research is needed to evaluate the stability of VR for tall fescue in other regions.

CONCLUSION

Enhancing irrigation efficiency through proper scheduling is essential in the semi-arid climate of inland southern California. Our study revealed that the typically recommended values of 80% ET_o, as applied by the Weathermatic controller, were insufficient to maintain the acceptable quality of 'Westcoaster' tall fescue during the summer in the region. Analysis of the collected VR and NDVI data indicated that approximately 100% ET_o is required to ensure the overall quality and health of tall fescue. Furthermore, TWRF estimations suggested that irrigation application of 110% ET_o is the minimum requirement under exceptionally high atmospheric evaporative demand. We also found that tall fescue can tolerate short periods of stress caused by lower irrigation applications. Further research is needed to investigate whether subsurface drip irrigation systems can help maintain tall fescue quality with lower irrigation application values by minimizing evaporative and runoff losses. The Weathermatic controller, equipped with on-site air temperature measurements, showed promising results by providing reliable ET_o estimations. Additionally, the long-term performance of the HS models demonstrated their accuracy in estimating ET_o compared to the standard CIMIS ET_o values.

ACKNOWLEDGMENT

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APPENDIX

Changes in NDVI and visual rating values over time for all treatments in the years 2017, 2018, and 2019.

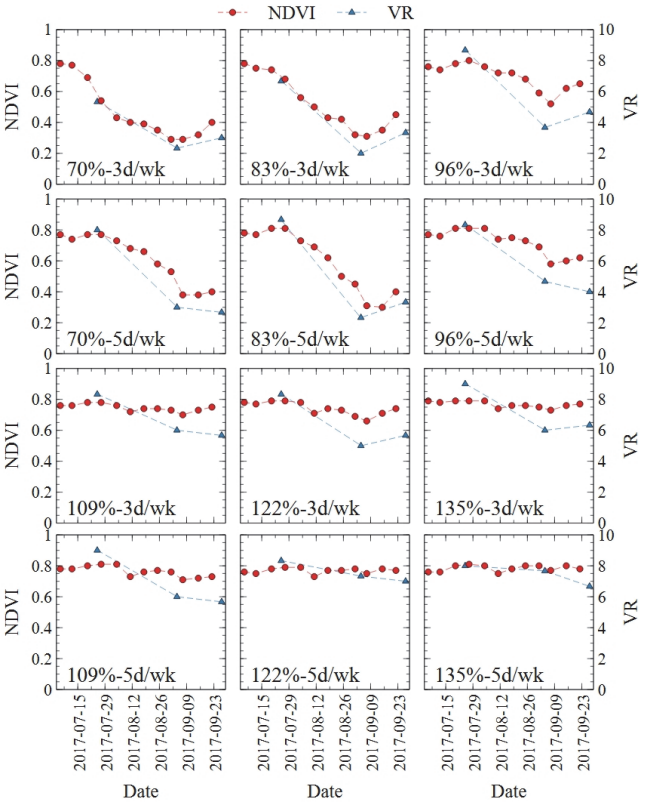

Figure A1. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments in 2017.

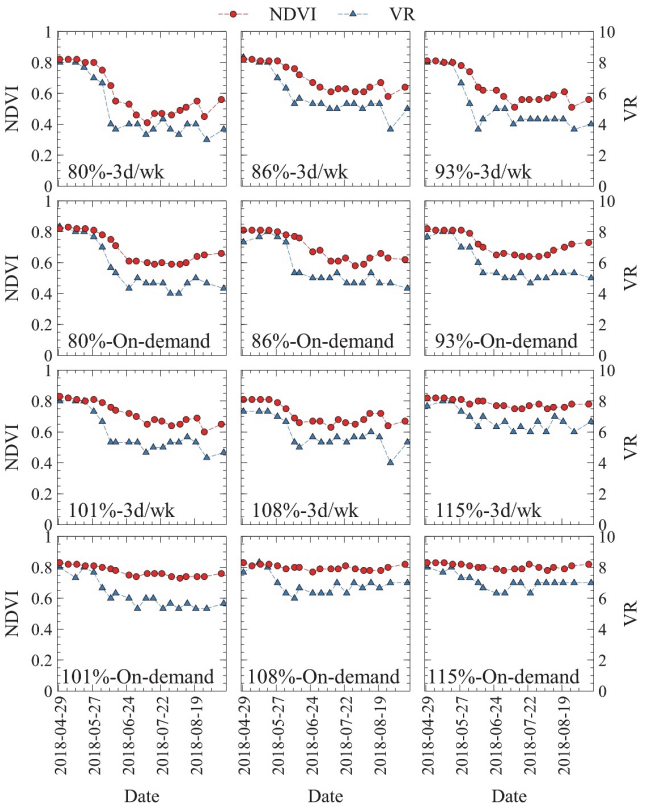

Figure A2. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments in 2018.

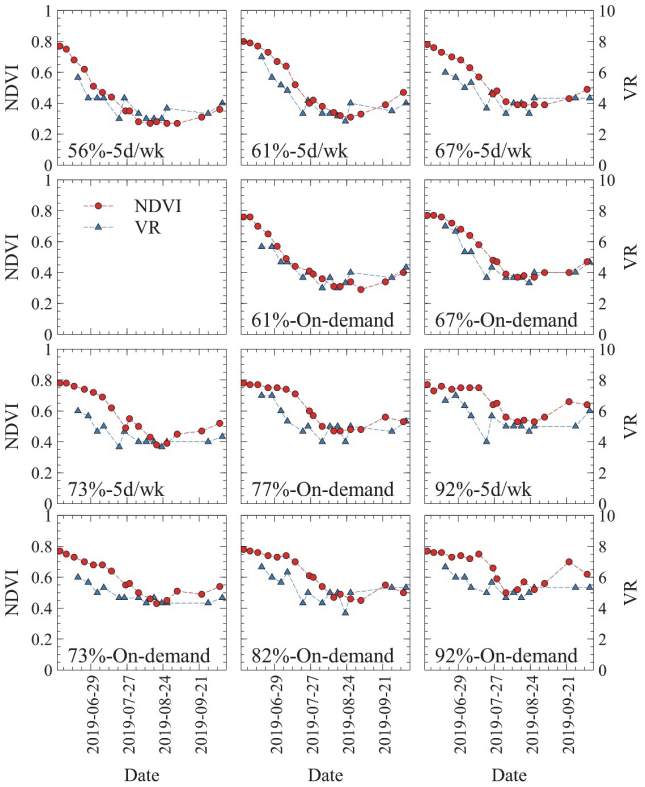

Figure A3. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments in 2019.